PROJECT ID: ELT260

Improving the Freight Productivity of a Heavy-Duty, Battery Electric Truck by Intelligent Energy Management

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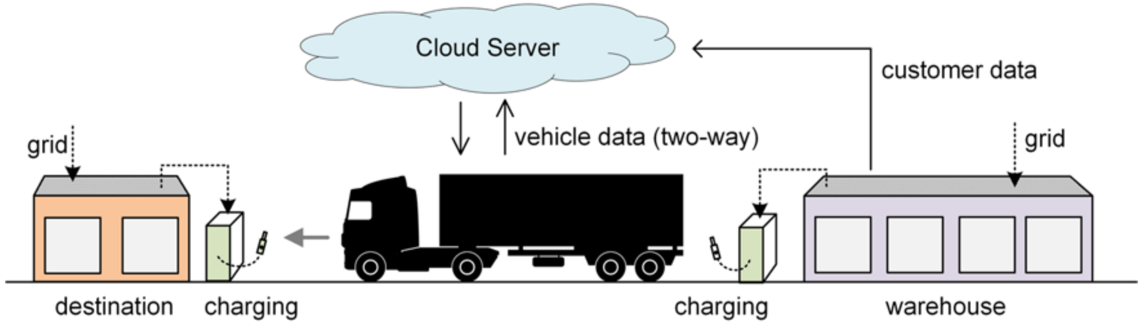
William Northrop (University of Minnesota)

June 23, 2022



2022 DOE Vehicle Technologies Office Annual Merit Review

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Project Overview

Timeline:

Oct. 2019 — June 2023

70%

Funding:

Total Project Cost: $4,869,889

- DOE funds: $3,799,536
- Industrial cost share: $1,070,353

- FY2020 funding: $468,245
- FY2021 funding: $3,279,285
- FY2022 funding: $1,109,292

Partners:

- University of Minnesota
- HEB Companies
- Murphy Logistics

Barriers:

- Total cost of ownership:
  - High purchase price and range of charge and payload
- Performance Validation:
  - Fleets need better performance data on Battery Electric Trucks, (BEVs), in real-world usage to validate the reliability of the vehicles
- Infrastructure Needs:
  - Infrastructure cost and planning complications

VOLVO

H-E-B

UNIVERSITY OF MINNESOTA
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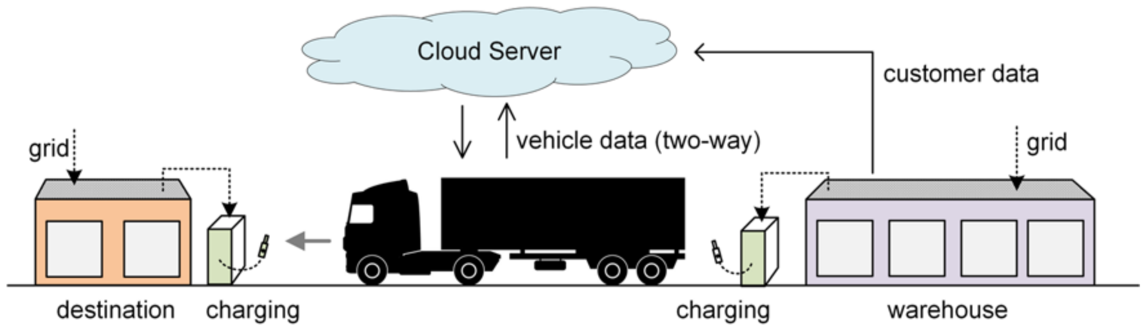
MURPHY LOGISTICS

Relevance

Impact:

Decrease the cost and time required for on-route charging, recommend energy efficient routing, and provide eco-driving recommendations to the operator.



Objective:

Research, develop, and demonstrate life cycle cost-effective Class 8 battery electric vehicles equipped with an intelligent Energy Management System (i-EMS) capable of commercial operations of ≥250 miles per day as well as increased efficiency and productivity when compared to baseline 2019 Mack and 2015-2020 Volvo heavy duty battery electric vehicle fleet performance.

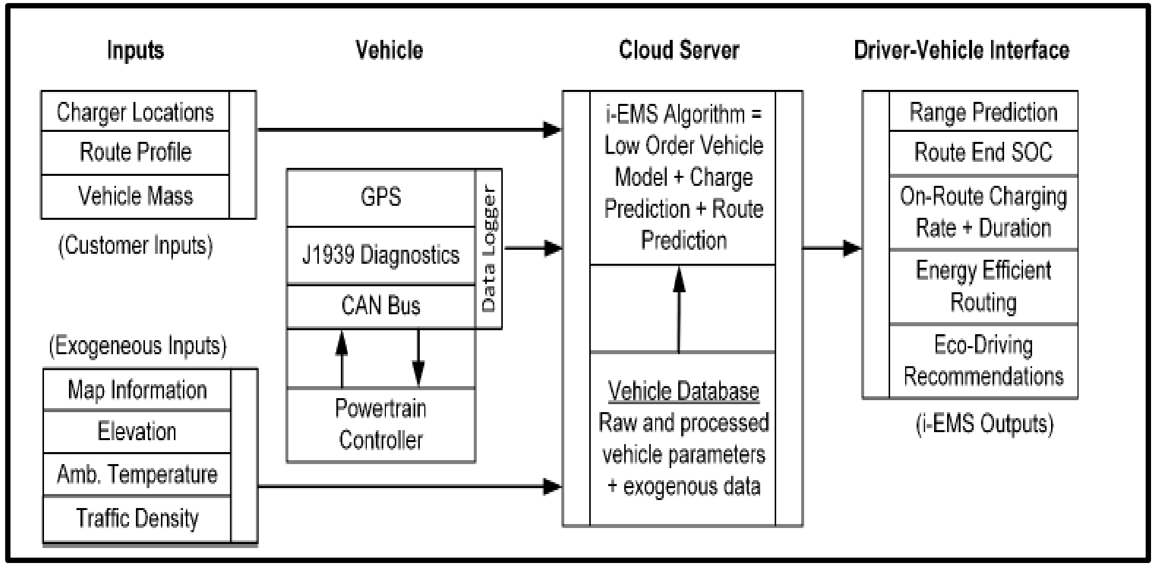
Milestones

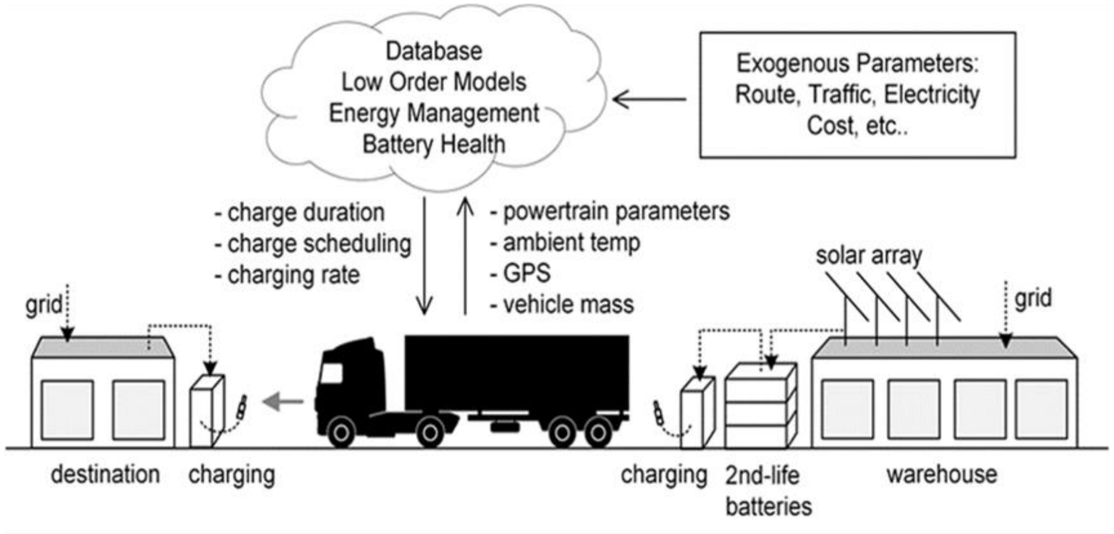
BP	Milestone	Type	Description	Status
Budget Period 1	Baseline database is created	Technical	Baseline database is created for all vehicle data and representative duty cycles are defined for the project	Completed
	Battery Electric Truck specification	Technical	Battery Electric Truck specification is ordered for build and delivery. Verified to Achieve Performance Measures, i.e., proper battery configuration.	Completed
	Initial battery electric truck simulation model	Technical	Initial, physics based battery electric truck model is complete	Completed
	Begin development of machine learning algorithm	Technical	Initial data and discussion allows for development of core algorithm to begin.	Completed
	Published verification plan and project requirement document	Go/No-Go	Published verification plan and project requirement documents outlining demonstration and evaluation plan is completed	Completed
Budget Period 2	Beta algorithms meet performance requirements.	Technical	Beta algorithms meet performance requirements to enable initiating of software development, i.e., identify and minimize on-route charging cost.	Completed
	Completed energy-efficient routing and driving algorithms	Technical	Completed energy-efficient routing and driving algorithms	Completed
	Complete driver interface	Technical	Complete driver interface app to install on test vehicles that communicates with vehicle and cloud server	Completed
	i-EMS performance	Technical	i-EMS performance is verified with actual truck operation per duty cycle definition	In-Process
	On-route charging locations	Go/No Go	Define necessary on-route charging locations for each customer site to accomplish the 250-mile range objective	In-Process

Approach

- Understand fleet partners' baseline operations and establish project duty cycles
- Combine physics-based truck model, battery information, utility demand charges and database parameters as inputs to a machine learning algorithm that will predict energy use, operational energy cost, and battery performance
- Implement i-EMS on 2 Battery Electric Vehicles, (BEVs), using a low-distraction screen to display charging and routing recommendations to operators
- Install vehicle charging locations at fleet partners
- Demonstrate i-EMS in daily operations with fleet partners covering both cold and hot-weather conditions

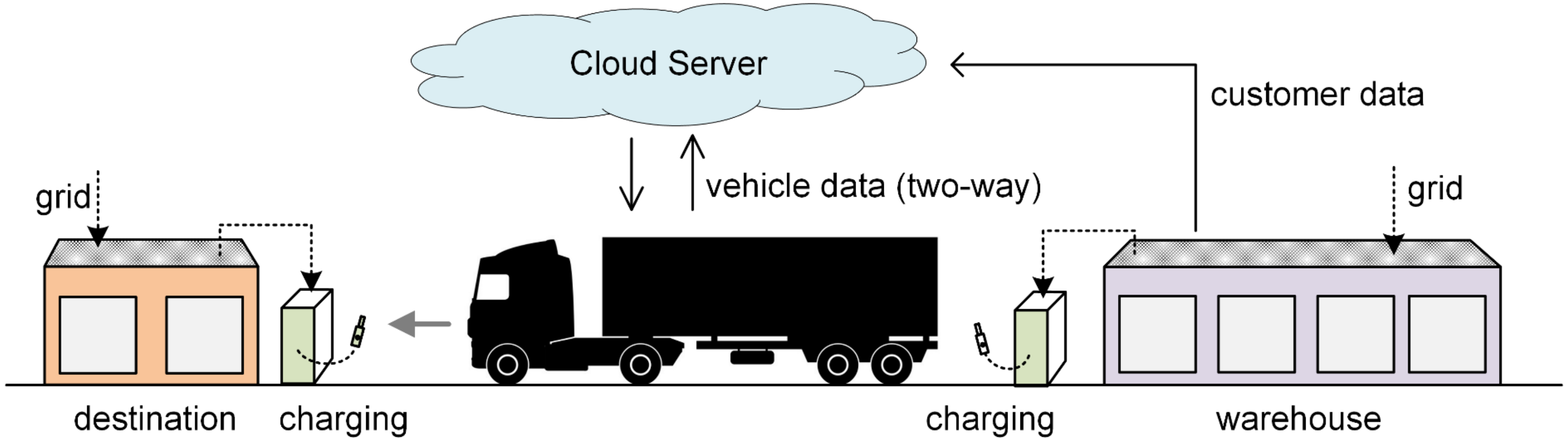
Schematic describing the flow of inputs and vehicle data





Technical Accomplishments and Progress
Overview

- Developed Elements of Intelligent Energy Management Strategy:
  - Task 2.1: Low-order physics model for fast energy estimation
  - Task 2.2: Initial machine learning algorithm for range and minimum charging prediction
  - Task 2.3: Eco-routing algorithm for use on filtered road network graph
  - Task 2.4-2.5: Charger placement optimization for individual trucks and routes
  - Task 2.6: Driver-vehicle interface (DVI) to relay i-EMS recommendations



BEV Specifications

- Truck #1 (NME-6)
  - GEN2 Batteries

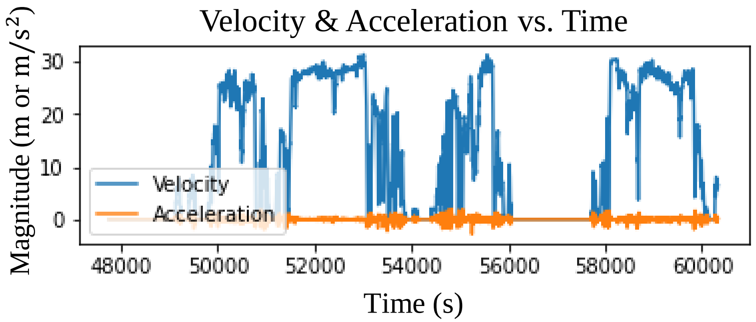
Description	NME-6 (Chassis# 604596) (Phase 1)	NME-8 (Phase 2)
INSTRUMENT CLUSTER GENERATION	-	IC-GEN1
CHARGING POWER	CHP150	CHP250
ENERGY STORAGE SYSTEM CAPACITY	ESS265K	ESS565K
ONBOARD CHARGER	ONCHAR	ONCHAR2
AIR COMPRESSOR DRIVING MOTOR	ACDM-AIC	ACDM-WC
COOLING ENERGY STORAGE SYSTEM	CESS-P	CESS-A
VEHICLE OVERSPEED,ALL COND,LOG	-	VOSAC70
ELECTRICAL SYSTEM	ELS-BP	ELS-BP+
PEDAL RSL SETTING	PRSL93	UPRSL

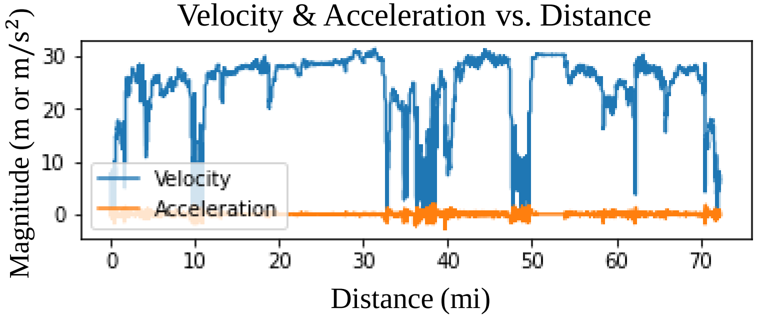
- Truck #2 (NME-8)
  - GEN3 Batteries

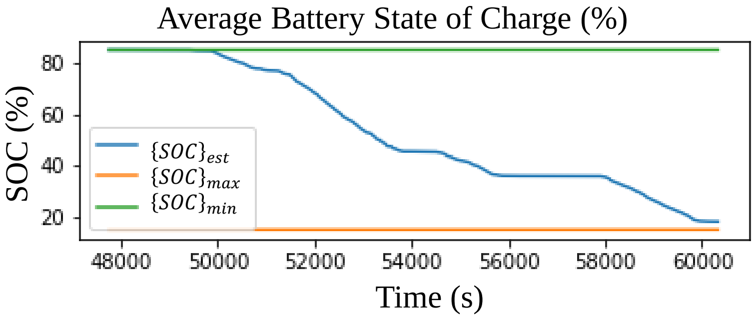
- Truck #1 was delivered to Minnesota December 2021
- Truck #2 is scheduled for delivery to San Antonio June 2022

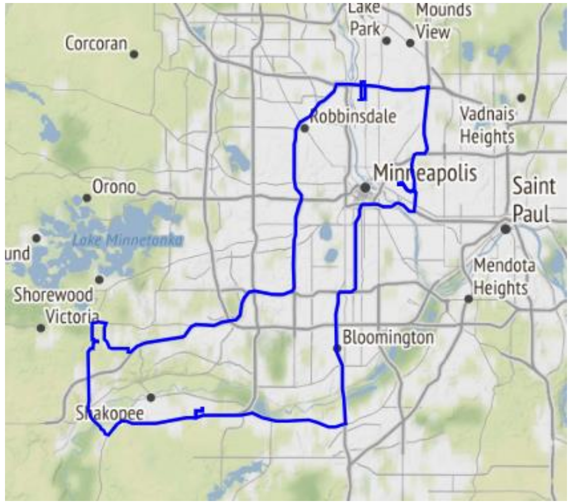
Technical Accomplishments and Progress
Task 2.1: Vehicle Physics Model

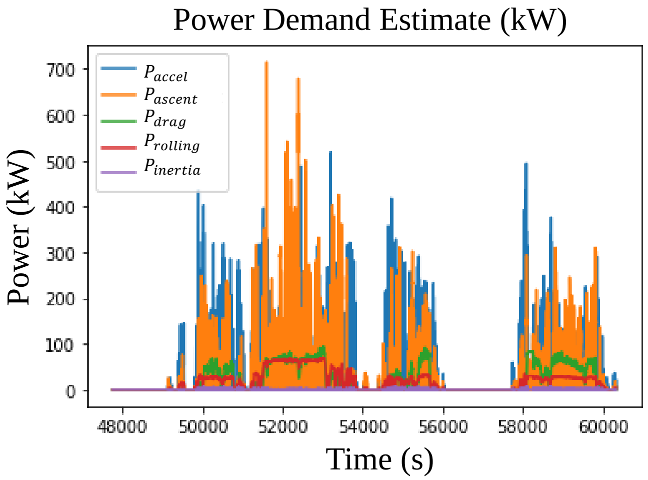
- Road Load Equation
  - Instantaneous Power
    - Acceleration
    - Ascent
    - Aerodynamic drag
    - Rolling resistance
    - Tire inertia
    - Braking friction losses
- Low-Order Battery Model
  - Current Delivered to Load
    - Open-circuit voltage
    - Internal resistance
    - Power demand







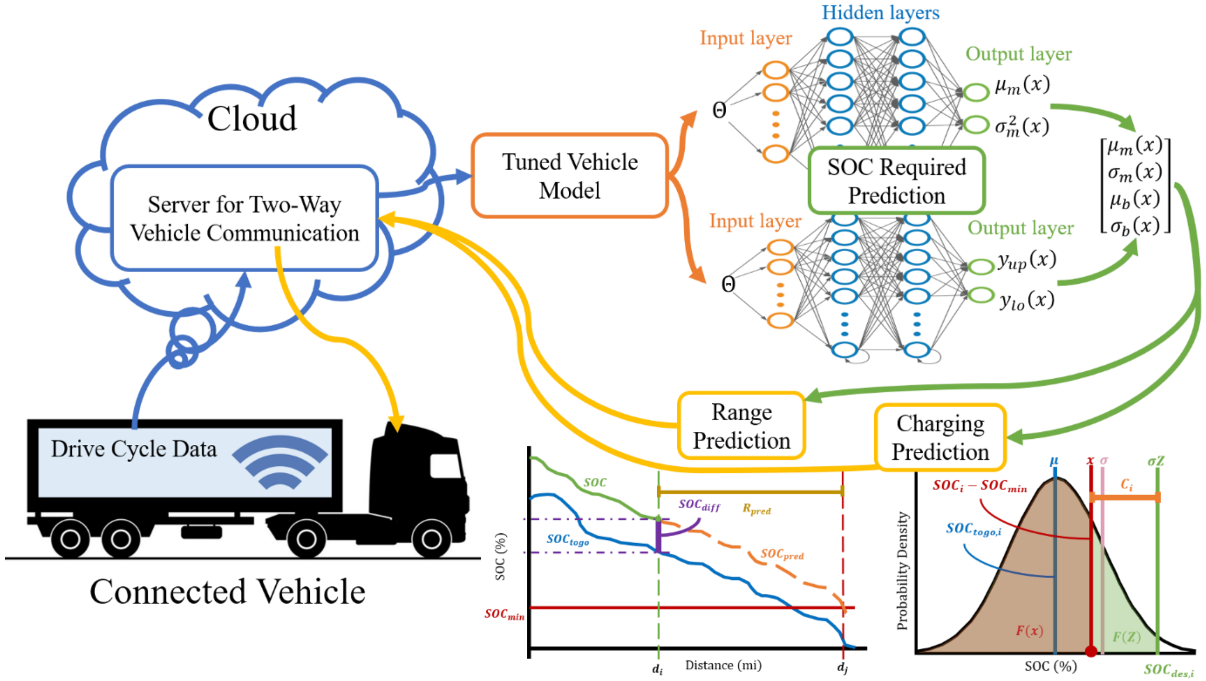


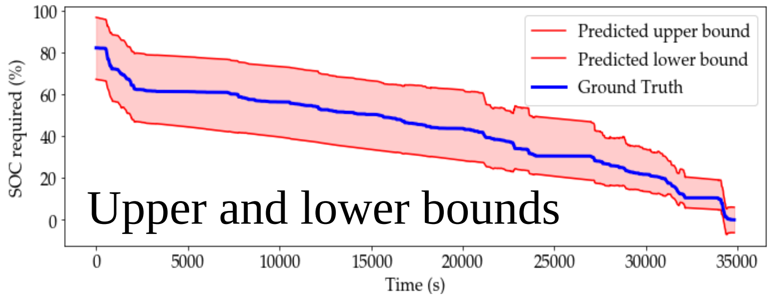


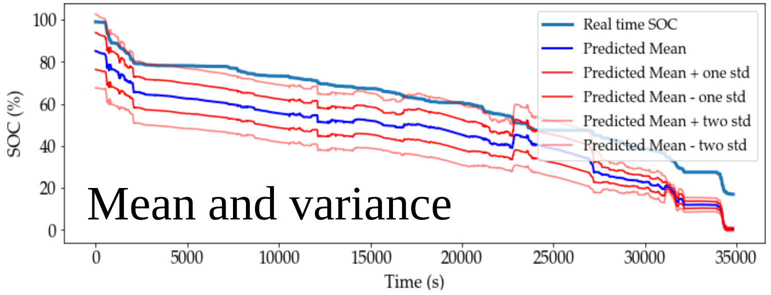
Technical Accomplishments and Progress

Task 2.2: Range and Charging Prediction

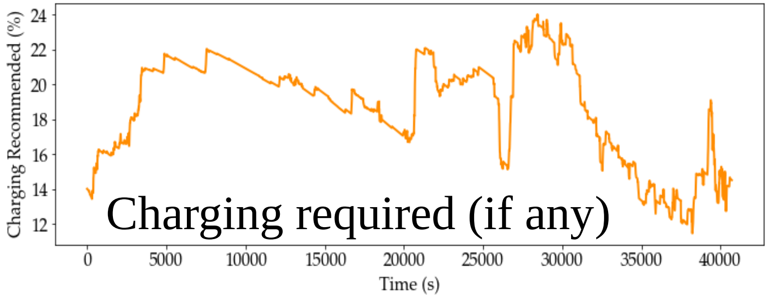
- Recurrent Neural Networks (RNNs)
  - Predict energy needed to complete route
  - Provide statistical confidence measures

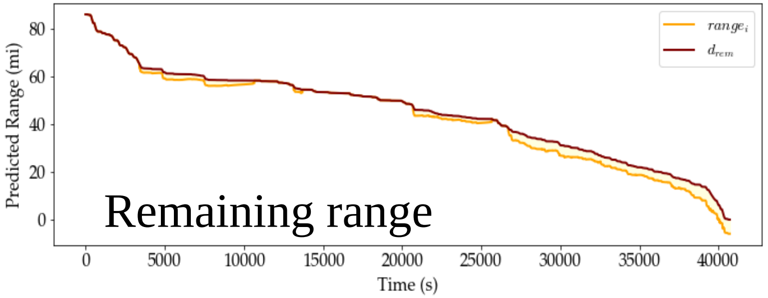






Energy needed to finish route



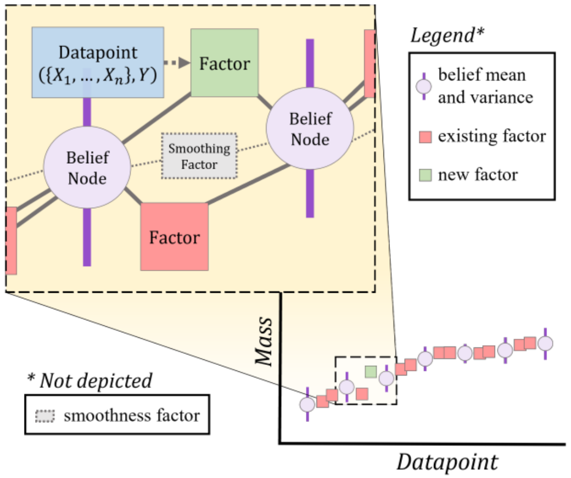


[1] Eagon, Matthew J., Daniel K. Kindem, Harish Panneer Selvam, and William F. Northrop. "Neural Network-Based Electric Vehicle Range Prediction for Smart Charging Optimization." *Journal of Dynamic Systems, Measurement, and Control* 144, no. 1 (January 1, 2022): 011110. https://doi.org/10.1115/1.4053306.

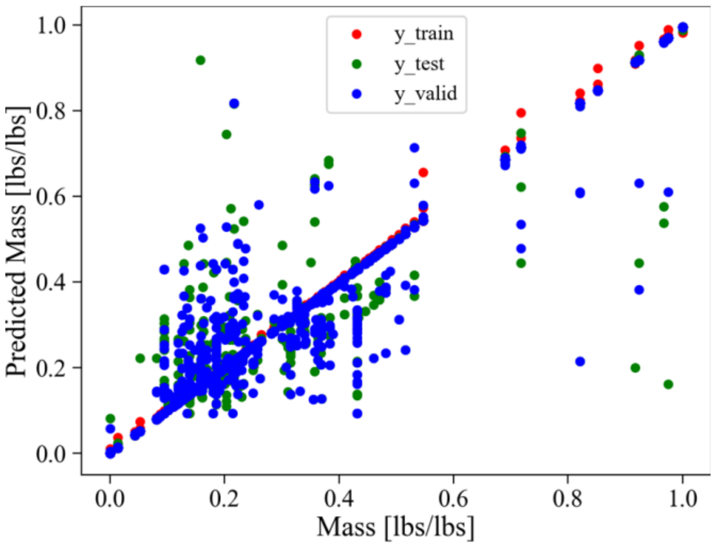
Technical Accomplishments and Progress

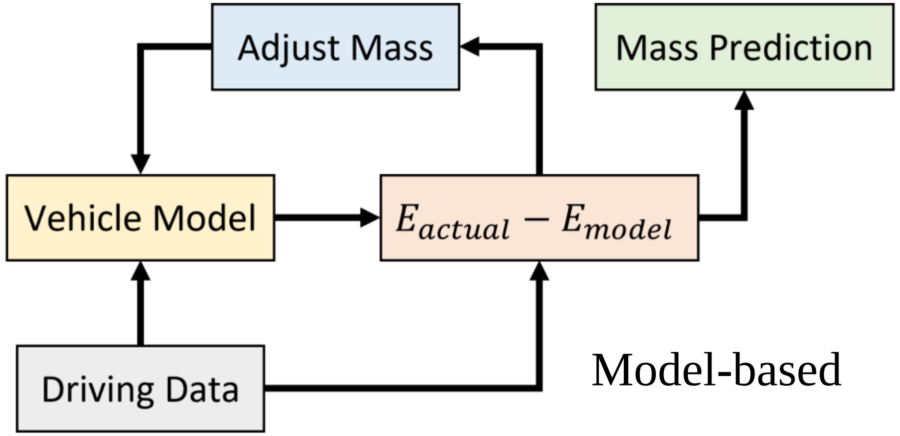
Task 2.2: Mass Prediction

- Three methods: online mass detection from driving data
  - Machine Learning: Deep Neural Network (DNN)
  - Statistical: Gaussian Belief Propagation (GBP)
  - Model-Based: Linear regression – compare expected and actual energy use



GBP





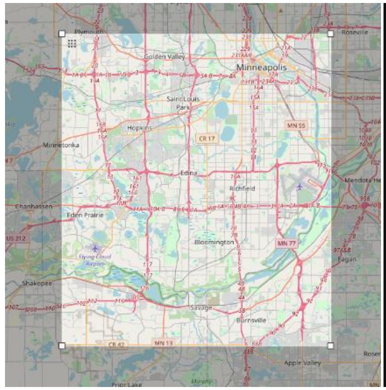
Model-based

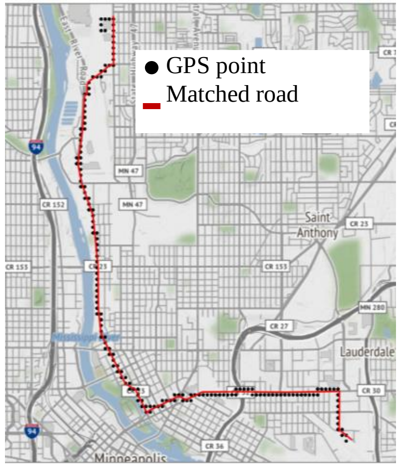
[2] Eagon, Matthew, Setayesh Fakhimi, Adam Pernsteiner, and William Northrop. "Mass Detection for Heavy-Duty Vehicles using Gaussian Belief Propagation." *2022 Intelligent Vehicles Symposium (IV)* (June 2022). Accepted for publication.

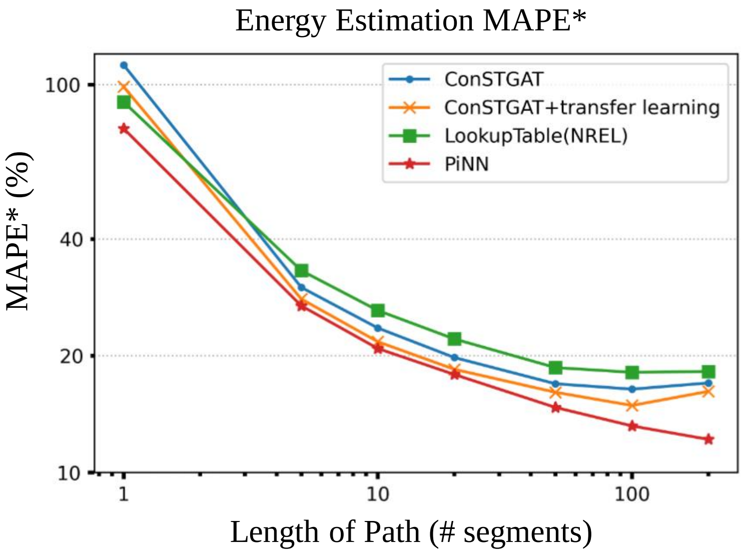
Technical Accomplishments and Progress

Task 2.3: Eco-Routing Algorithm

- Map-matching from GPS data
  - Road network graph construction
  - Match driving data to network graph
- Energy Estimation Methods
  - Energy Estimation Lookup Table
    - Energy estimation for similar road segment groups
  - Transfer Learning
    - ConSTGAT (State-of-the-art for time travel estimation)
  - Physics-informed Deep Neural Network (PiNN)
    - Energy and time estimation for individual paths
    - See next page for architecture
- Routing Algorithm
  - A* pathfinding algorithm
    - Heuristic based on [3]







* Mean Absolute Percentage Error

[3] Li, Yan, Pratik Kotwal, Pengyue Wang, Yiqun Xie, Shashi Shekhar, and William Northrop. 2020. Physics- guided Energy-efficient Path Selection Using On-board Diagnostics Data. *ACM Trans. Data Sci.* 1, 1, Article 1 (January 2020), 29 pages. https://doi.org/10.1145/3406596

Technical Accomplishments and Progress

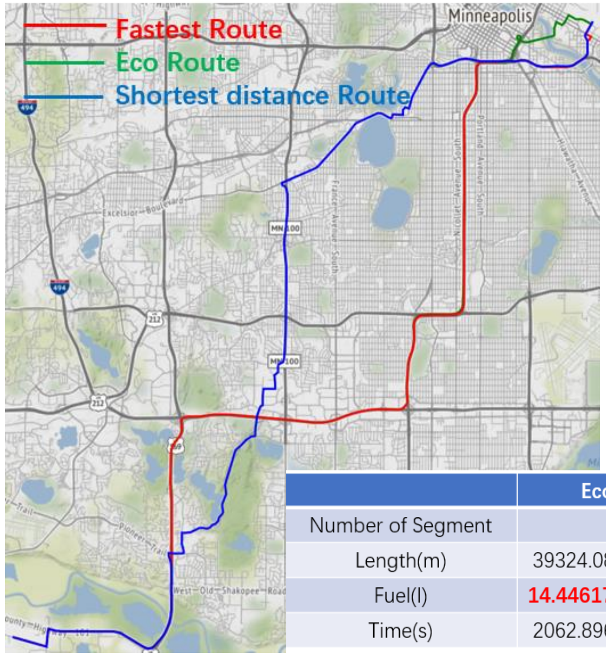
Task 2.3: Eco-Routing Algorithm

- DNN Architecture
  - Energy estimation
- Example Route
  - Path finding

Attributes

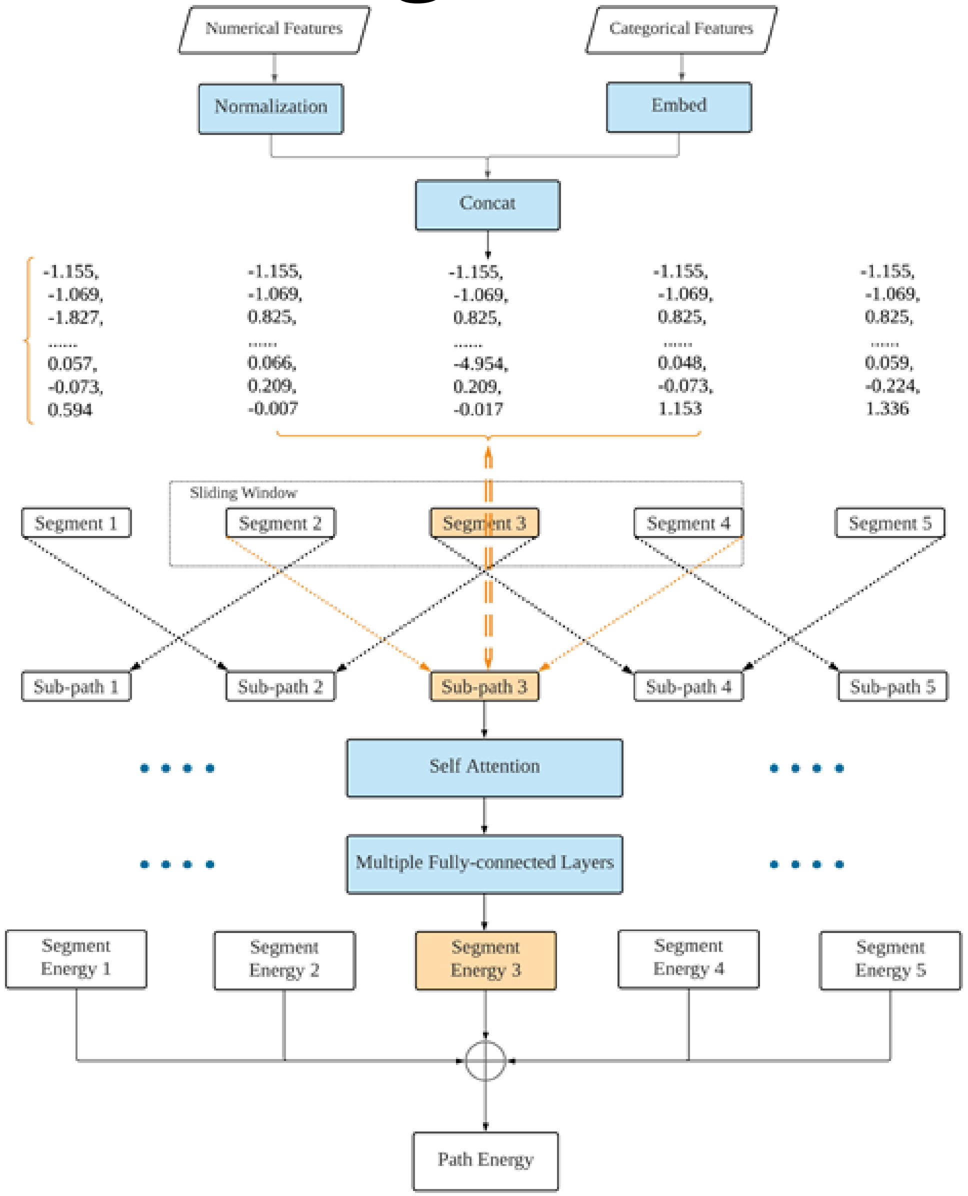
- Road length
- Road type
- Speed limit
- Turning angle
- Elevation change
- OBD data
- Day of week
- Time of day
- …

Input Data
26 dimensions



Output

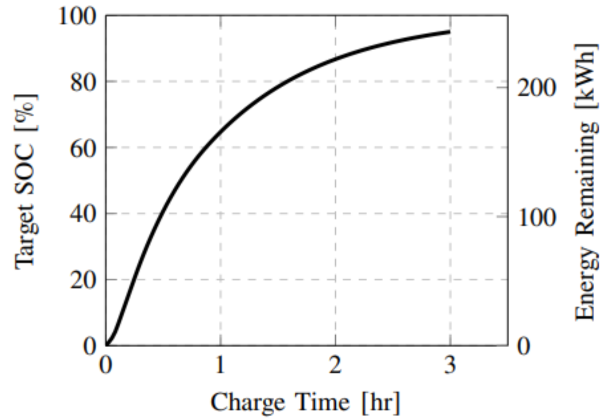
	Eco Route	Shortest Distance Route	Fastest Route
Number of Segment	81	155	70
Length(m)	39324.087999999996	37434.512	38967.602
Fuel(l)	14.446175426244736	18.433458421379328	15.14326499029994
Time(s)	2062.8963108062744	2744.7623907357647	1708.2627217806876

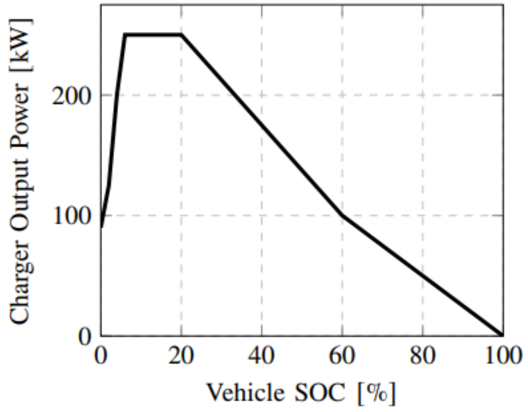


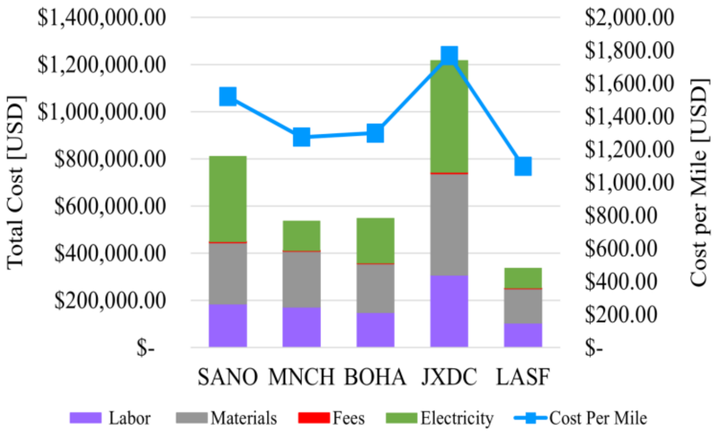
Technical Accomplishments and Progress

Task 2.4-2.5: Charger Placement Algorithm

- Mixed Integer Programming
  - Optimize Placement Based Upon Expected Demand
  - Also Tested: Genetic Algorithm, K-Means Clustering
  - Incorporates Model-Based Driving Simulation
    - Vehicle Model
      - Drives along routes
      - Determines hotspots for charging needs
    - Charger Model
      - Charge on-route vehicles
    - Cost Model
      - Labor
      - Charger (Materials)
      - Electricity
  - Increases Number of Chargers Until...
    - Minimum Portion of Routes Are Feasible
    - Maximum Budget is Reached
    - Other constraints also possible







[4] Eagon, Matthew, Setayesh Fakhimi, George Lyu, Brian Lin, Audrey Yang, and William Northrop. "Model-Based Framework to Optimize Charger Station Deployment for Battery Electric Vehicles." *2022 Intelligent Vehicles Symposium (IV)* (June 2022). Accepted for publication.

Technical Accomplishments and Progress

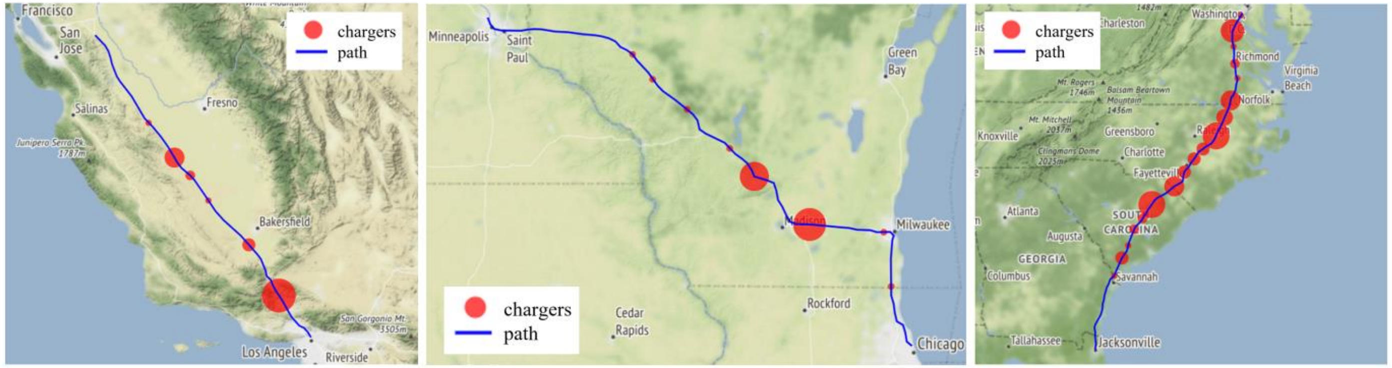
Task 2.4-2.5: Charger Placement Algorithm

- Example results
  - Max chargers-per-station: 10
  - Max wait time: 15 min
  - Min route coverage: 95%
  - Budget: unconstrained

	Length [mi]	Stations	Chargers	Route Coverage	Max Wait [hr]	Max Chargers
SANO	533	12	64	96.67%	0.246	10
MNCH	421	8	26	95.33%	0.249	9
BOHA	422	8	36	96.00%	0.220	9
JXDC	689	18	73	98.67%	0.240	8
LASF	307	6	26	96.67%	0.200	6

(a) SANO
San Antonio to New Orleans

(b) BOHA
Boston to Harrisburg



(c) LASF
Los Angeles to San Francisco

(d) MNCH
Minneapolis to Chicago

(e) JXDC
Jacksonville to Washington DC

[4] Eagon, Matthew, Setayesh Fakhimi, George Lyu, Brian Lin, Audrey Yang, and William Northrop. "Model-Based Framework to Optimize Charger Station Deployment for Battery Electric Vehicles." *2022 Intelligent Vehicles Symposium (IV)* (June 2022). Accepted for publication.

Technical Accomplishments and Progress

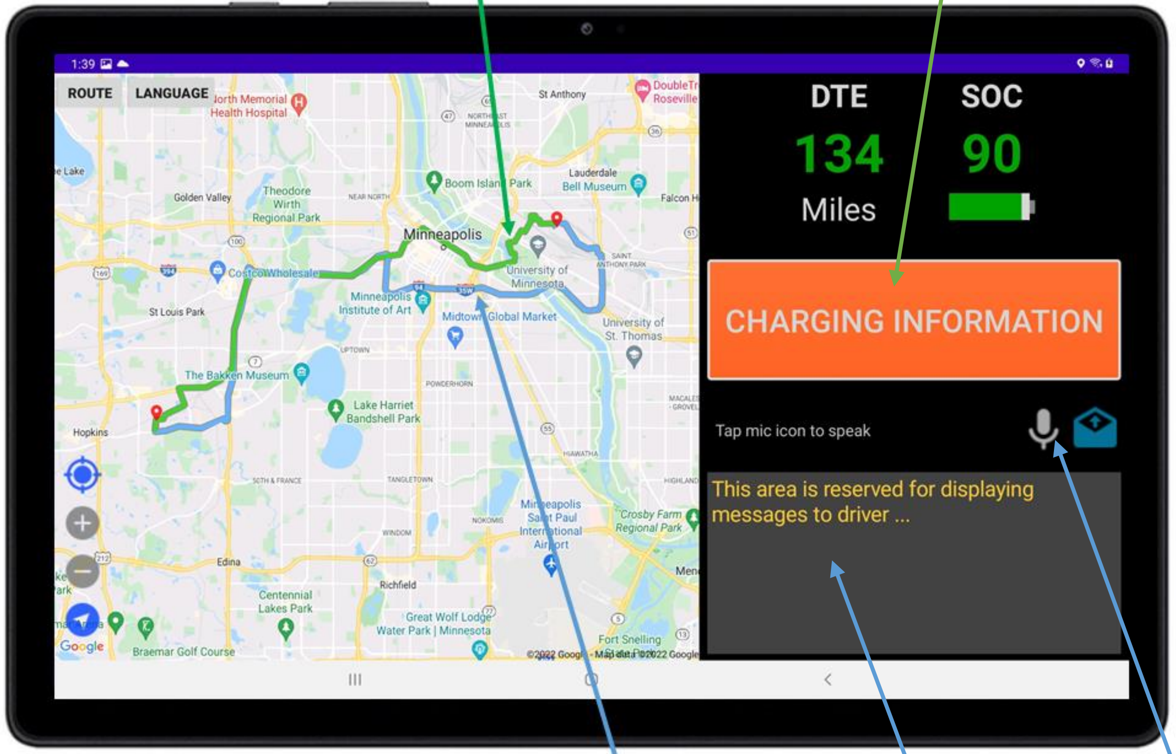
Task 2.6: Driver-Vehicle Interface (DVI)

- UI Design Complete, Ready for Install

Main Screen: Routing + Energy Info

Eco Route (Green)

Screen to display info while charging



Google Route (Blue)

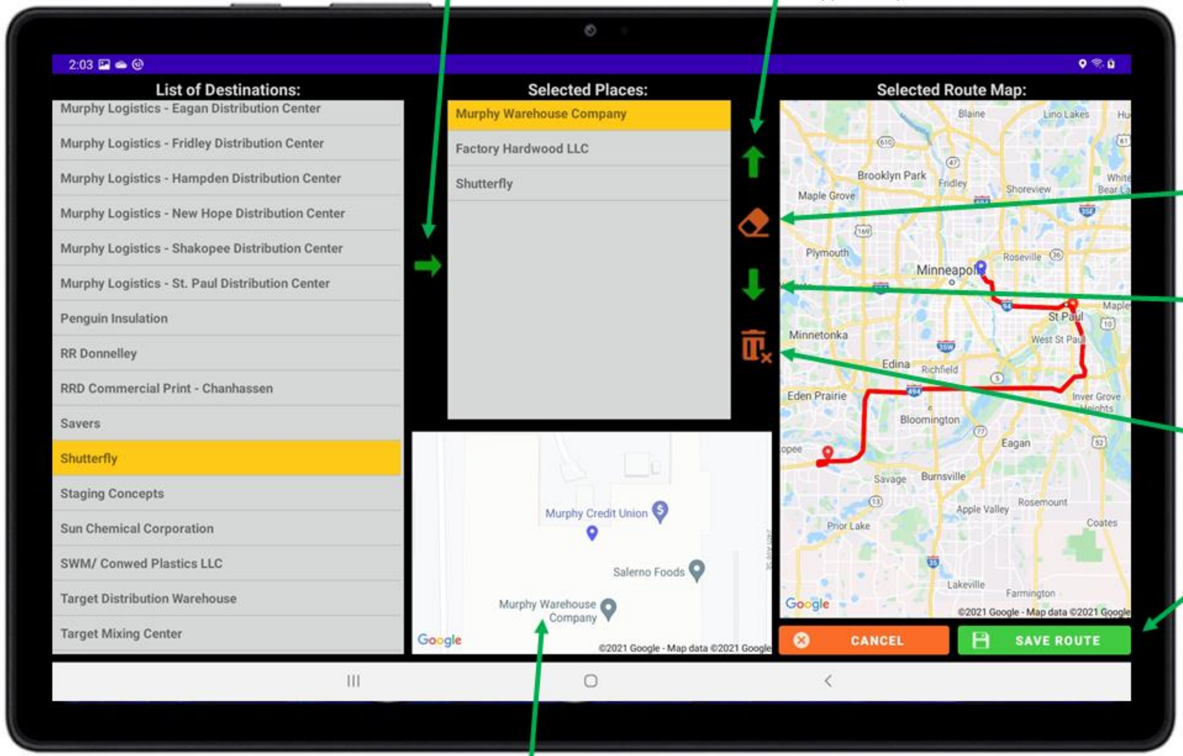
Display messages to driver

Transcribe driver feedback (voice msg)

Routing Screen: Choose or Build Route

Add a waypoint

Move the highlighted waypoint up



Remove the highlighted waypoint

Move the highlighted waypoint down

Delete ALL waypoints

Save the created route

Zoom-in map of the selected waypoint location

Collaboration and Coordination

Organization	Key Contributions
Volvo	Principle Investigator, Contract Management, Project Management and engineering resources for truck operation, data collection and route simulation
University of Minnesota	Vehicle to cloud data management, algorithm development, data analytics, secondary driver display
Gilbarco	Electric charging support, installation of chargers
HEB Companies	Fleet testing, operational data, driver feedback
Murphy Logistics	Fleet testing, operational data, driver feedback

Remaining Challenges and Barriers

- Technical Challenges
  - In-house model validation with results from OEM models/driving data
    - Determining the effects of temperature on battery performance
    - Output power limiting behavior for charging stations
  - Integrate models into driver-vehicle interface
  - Speed up eco-routing execution time
  - Quantify effects of traffic on eco-routing performance
  - Develop logic for re-routing decisions

- Other Barriers
  - Delays in vehicle production → delivery → testing → validation
  - Defining accurate operational cost parameters
  - Identifying best routes for use in long-haul dominated trucking fleets

Proposed Future Research

- FY22: Testing and Operational Cost Analysis
  - Develop reinforcement learning agent for high-level decision making (e.g. rerouting to charge)
  - Finalize charger placement solution for vehicle fleets
  - Deploy algorithms on driver-vehicle interface for testing and validation
  - Tailor developed models to initial testing data
  - Develop and investigate correctness of operational cost model
  - Evaluate most effective EV use-case for fleet partners
  - Gather feedback from vehicle operators on driver-vehicle interface

- FY23: Extended Testing and Validation
  - Extend test routes with the addition of an on-route charging station
    - Demonstrate 250+ miles of daily driving
  - Determine final accuracy of developed models
    - Predictions: Energy usage, mass, remaining range, minimum charge needed,
  - Evaluate impact of extreme ambient conditions (i.e. TX summer, MN winter) on performance
  - Validate effectiveness of eco-routing algorithm, i-EMS energy and cost savings

Any proposed future work is subject to change based on funding levels

Project Summary

- The goals of this project are aligned to the key barriers of total cost of ownership, performance validation and infrastructure needs as pertaining to the operation of a Heavy-Duty BEV.

- In this reporting period analysis has been performed on the baseline data to develop the i-EMS technologies that will be used to recommend energy efficient routing and provide eco-driving recommendations to the operator.

- In this reporting period two BEV were delivered to the fleet partners Murphy and HEB, and feedbacks from the driver are positive:
    - “The drivability is very good; the high torque is a nice benefit”
    - “Normally it’s quiet, the interior noise is a lot less than a conventional, you will still hear the tires, the compressors”
    - “I think the drivers will like the vehicles, and find it hard to go back to a conventional”